194.077 Applied Deep Learning
Assignment 3 - Weather Phenomena Classification

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1 Introduction

In the persistently evolving field of Machine Learning, Computer Vision has gained enormous popularity thanks to its ability to interpret visual information in a meaningful way. In the realm of Visual Computing, this project proposes an Image Classification task using Deep Learning methods on the Weather Phenomena Dataset (WEAPD [1]) to classify diverse weather phenomena.

2 Dataset

The dataset comprises 6862 photos, with 11 classes: dew, fog/smog, frost, glaze, hail, lightning, rain, rainbow, rime, sandstorm and snow. This dataset includes a higher number of classes compared to other traditional weather classification datasets. The class with the most samples is 'rime', with 1160 images, by contrast, 'rainbow' accounts for only 238 images, making this an imbalanced dataset. To deal with this shortcoming techniques such as data augmentation must be adopted. All samples are color images in JPG format that vary in size.

3 Related Works

In image classification tasks, transfer learning is commonly applied, this is particularly useful in solving the problem of insufficient training data. Some of the best results achieved on this dataset leverage the VGG16 architecture.
The authors of the WEAPD dataset explain their approach for Weather Classification in the 2021 paper '*Classification of Weather Phenomenon From Images by Using Deep Convolutional Neural Network* [2]'. They introduce the MeteCNN architecture, a modified version of the VGG16 architecture, which achieves impressive performance with 92.68% accuracy. This architecture includes improvements like the use of Squeeze-and-Excitation (SE) modules and dilated convolutions. A more recent paper published in 2024, '*Enhanced Multi-Class Weather Image Classification Using Data Augmentation and Dynamic Learning on Pre-Trained Deep Neural Net* [3]' uses transfer learning to achieve comparable results. They employ data augmentation techniques and fine-tuning to obtain 92.10% accuracy.

4 Problem Formulation

The problem this project aims to address is to classify diverse weather phenomena based on images using a *balanced* dataset for training and *increasing the number of classes.* By improving the model's ability to recognize various weather conditions accurately, the goal is to enhance its performance across all classes, particularly the underrepresented ones.

Such an efficient weather classification model can be useful in a variety of real-world applications, including disaster management systems, agriculture, autonomous vehicles, renewable energy resource management, and environmental monitoring. Accurate weather classification can help mitigate risks, optimize resource usage, support decision-making in the above mentioned fields.

5 Project Idea

This project falls into the 'Bring your own method' type for this Assignment: it uses a pre-existing dataset and model architecture, aiming to achieve performance improvements.

Objectives:

- **Expand the number of weather phenomena** classes by gathering additional data samples, as suggested by the dataset's authors for future works.
- **Explore additional data augmentation techniques** to address the data shortage for some classes.
- **Re-implement the EfficientNetB0 Model**, performing hyper parameters tuning, on parameters such as learning rate, batch size, dropout and experimenting with the loss function.

6 Project Implementation

Dataset Two new classes, *Tornado* and *Aurora*, were introduced. Data samples were downloaded from Bing using the 'bing-image-downloader' library. Random oversampling was used to overcome the class imbalance for underrepresented phenomena in the original dataset.

Additionally, data augmentation techniques, such as flipping, and adjusting contrast or brightness were applied on a small percentage of the data in the training set. As a result, the total number of training samples increased from 4899 to 15387.

Model Architecture The family of *EfficientNet models* represents a series of deep neural network architectures that redefine efficiency and performance for image classification. EfficientNet achieves impressive results by employing **compound scaling**, which uniformly scales the network's depth, width, and resolution. This family includes architectures ranging from EfficientNetB0 to EfficientNetB7, which differ in terms of an increase in depth, width and resolution, allowing progressive performance enhancements. For this project, the *EfficientNetB0* architecture was chosen for implementation due to its reduced number of parameters.

The model was implemented using the TensorFlow and Keras APIs, which allow building, training and evaluating deep learning models in a faster and simpler way. The core building block of the architecture, *MobileNetV2's Mobile Inverted Residual Block*, was developed as a standalone module. This module was then configured with varying parameters to construct the layers of the model.

The final architecture showed a total of 3.5M trainable parameters, compared to the actual reported 5.3M parameters.

Model Tuning The model tuning was performed for three hyper-parameters :

- Activation Function
- Learning Rate
- Optimizer

Random search was utilized to determine the optimal combination of these hyper-parameters.

7 Work-Breakdown

The actual time spent on each task of the project in terms of working hours was the following:

- **Dataset Retrieval and Scientific Paper Research**: 3 hours
- **Data Preprocessing, Model Development and Training**: 17.45 hours
- **Model Improvements and Fine-Tuning**: 16.10 hours
- **Final Testing and Evaluation**: 0.30 hours
- **Report and Results Presentation**: 6.30h

Surprisingly, the time estimates for each task were either accurate or very close to the actual time spent.

8 Results

The best hyperparameters identified were consistent with those reported in scientific literature:

- Activation function: Swish
- Learning rate: 0.001
- Optimizer: Root Mean Squared Propagation (RMSProp)

The model was trained using the RMSProp optimizer, with a desirable target of achieving a loss below 0.4 on the test set.

Training was conducted for a total of 32 epochs and the performance metrics were as follows:

- Training accuracy: 93%
- Validation accuracy: 87%
- Test accuracy: 91%
- Test loss: 0.27

9 Observations

During the test-validation split, an error occurred when setting the split percentage to 15% (0.15). This resulted in the following distribution for the original WEAPD dataset: 68% for training, 12% for validation, and 20% for testing. This error caused an imbalance in the number of validation and test samples and could potentially explain the slightly lower performance on the validation data. In future work the split should be adjusted to ensure a more balanced distribution between validation and test data.

10 Conclusions

In this project, several key insights relevant for image classification tasks emerged.

First, data augmentation proved essential in addressing class imbalance, by artificially increasing the representation of underrepresented classes.

The choice of EfficientNetB0 as the model backbone enabled the experiments to be run on a CPU system, balancing efficiency and performance.

Random search for hyperparameter tuning provided a useful method for finding optimal settings,but at the same time required considerable execution time. The use of bing-image-downloader was a great way to quickly fetch samples online, though manual verification of the downloaded images was necessary to ensure they were consistent with the associated class label.

Finally, the resulting Weather Phenomena demo application serves as an effective tool for weather image classification, leveraging the weights trained during this project by fetching them dynamically from the web. It performs predictions on weather phenomena with similar accuracy to the one reported in previous literature.

References

[1] H. Xiao, "Weather phenomenon database (WEAPD)," 2021. [Online]. Available: https://doi.org/10.7910/DVN/M8JQCR

[2] H. Xiao, F. Zhang, Z. Shen, K. Wu, and J. Zhang, "Classification of weather phenomenon from images by using deep convolutional neural network," *Earth and Space Science*, vol. 8, 05 2021.

[3] D. Chattoraj, A. Chatterjee, S. Ghosh, A. Ghosh, and E. Ientilucci, "Enhanced multi-class weather image classification using data augmentation and dynamic learning on pre-trained deep neural net," 08 2024, pp. 459–464.